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This is the final report for our AFOSR sponsored project: Information Fusion for High Level Situation Assessment and Prediction. Through this project, we developed a probabilistic framework for performing high level information fusion. In addition, we developed algorithms for performing active information fusion to improve both fusion accuracy and efficiency so that decision making and situation assessment can be made in a timely and efficient manner. Finally, we applied the framework and the algorithms to a military application to demonstrate its feasibility and validity for high level information fusion.

In this report, we first summarize our technical accomplishments, followed by a discussion of transitions related to this project. The related paper reprints are attached with this report. In addition, the latest paper reprints, publications, and software demos from this project may also be found at http://www.ecse.rpi.edu/~cvrl/lwh/ .

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INFORMATION FUSION FOR HIGH LEVEL SITUATION ASSESSMENT AND PREDICTION

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Final Report for AFOSR Project
F49620-03-1-0160

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1. Summary

This is the final report for our AFOSR sponsored project: Information Fusion for High Level Situation Assessment and Prediction. Through this project, we developed a probabilistic framework for performing high level information fusion. In addition, we developed algorithms for performing active information fusion to improve both fusion accuracy and efficiency so that decision making and situation assessment can be made in a timely and efficient manner. Finally, we applied the framework and the algorithms to a military application to demonstrate its feasibility and validity for high level information fusion.

In this report, we first summarize our technical accomplishments, followed by a discussion of transitions related to this project. The related paper reprints are attached with this report. In addition, the latest paper reprints, publications, and software demos from this project may also be found at http://www.ecse.rpi.edu/~cvrl/lwh/ .

2. Introduction

There are several challenges facing information fusion for situation awareness and decision making for military applications. First, sensory data generally involves multiple data types such as various sensory signals (radars either at the same or different frequencies as well as EO/IR sensors), circumstantial evidence, geographical information, subjective knowledge, and various constraints. They provide information at different levels of abstraction. They are often uncertain, ambiguous, and local. Second, for many military domains, the world situation is often dynamic and unfolds over time. The sensory observations also evolve over time to reflect changes in the world. To correctly assess and interpret the world situation, an adaptive system is needed that can reason over time since it is often the temporal changes that provide crucial information about what we try to infer and understand. Third, many military applications are also often constrained by limited time, resources, and complex environments. Given a vast amount of sensory data, it is important that fusion be carried out in an efficient and economical manner to avoid unnecessary or unproductive sensor actions and computations so that decision about the situation and threat can be made in a timely and efficient manner. A high level fusion system that is dynamically selective, purposive and sufficing is therefore more suitable. This can be achieved through active fusion, which involves deliberate sensor management to achieve efficient, timely, and often more accurate information fusion. Specifically, active fusion answers the following questions: what information to acquire next to minimize the uncertainty of situation assessment and to maximize the overall expected utility of decision making, what sensors can be used to acquire the information efficiently, timely, and safely, when to activate the sensors, and how to fuse the acquired sensory data efficiently. The goal of this research is to develop a high level multi-sensory fusion system to address all these challenges.

Figure 1 illustrates an active fusion framework. The framework consists of a set of information sources (sensors) monitoring the world, a sensor selection mechanism, a fusion methodology, the results of fusion (e.g., situation understanding), and a decision-making mechanism for identifying a set of actions that respond to the fusion results. A complete active fusion procedure includes deciding a sensor set that achieves the optimal trade-off between its cost and benefit, activating the identified sensors, integrating the acquired sensory data, and making decisions based on the fusion results.

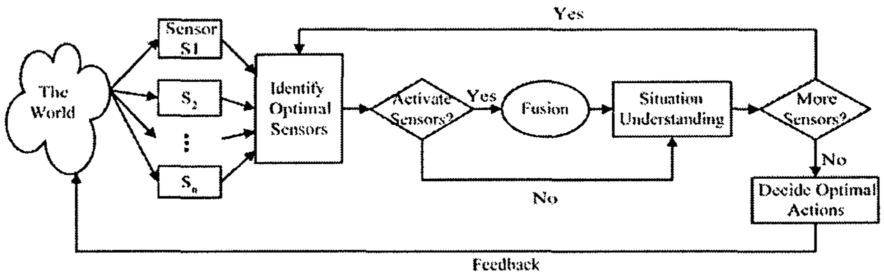


Figure 1: An active fusion framework

The work for this project consists of three parts: The first part focuses on developing and implementing a probabilistic framework for representing and integrating sensory data of different modalities at different levels of abstraction. One component of this part of the work is the development of a machine learning method for automatic parameterization of the framework for a particular application. The second part is to develop the theories and algorithms for performing active information fusion. This requires first defining a sensor selection criterion, developing computational methods to efficiently compute the criterion, developing algorithms to perform efficient sensor selection using the criterion, and finally developing methods to efficiently fuse the acquire the sensory data. The third part of this research is to demonstrate the proposed framework and algorithms for a military application with a prototype software. We have made significant progress in each of these three areas as detailed below.

3. An Unified Probabilistic Framework for High Level Information Fusion

Knowledge in a military domain is complex, uncertain, and dynamic. We need a framework that can accurately model the incomplete/uncertain world knowledge and that provides a mechanism for systematically and actively integrating dynamic information from disparate sources. The Dynamic Bayesian Networks (DBNs) appear ideal for meeting these requirements. DBNs are probabilistic graphs with nodes representing random variables and links representing the casual relationships among the connected nodes. Rooted firmly in the long-established field of probability theory, DBNs can systematically and actively combine corrupted sensory inputs of different modalities occurring over different time frames to produce a consistent, coherent, and accurate global picture of the underlying events and to generate appropriate response recommendations. Knowledge modeling using DBNs involves identification and representation of the sensory information, contextual information, hypotheses (what we want to infer), and their dependencies as well as their uncertainties and dynamics.

Specifically, DBNs provide a coherent and unified hierarchical probabilistic framework for representing and integrating information from diverse and correlated sources, including sonar, radar, images, tactical information, and knowledge expressed by domain experts or synthesized through discovery techniques. Furthermore, DBNs dynamically evolve and grow to accommodate the new happenings and to assess the current situation not only based on the current information but also utilize information produced during previous time frames, as alternative scenarios are reinforced or ruled out dynamically. Figure 2 shows an example of using DBN to integrate various sensory data to infer enemy intent. Details about this work may be found in [Zhang&Ji06a,Liao&Ji07b].

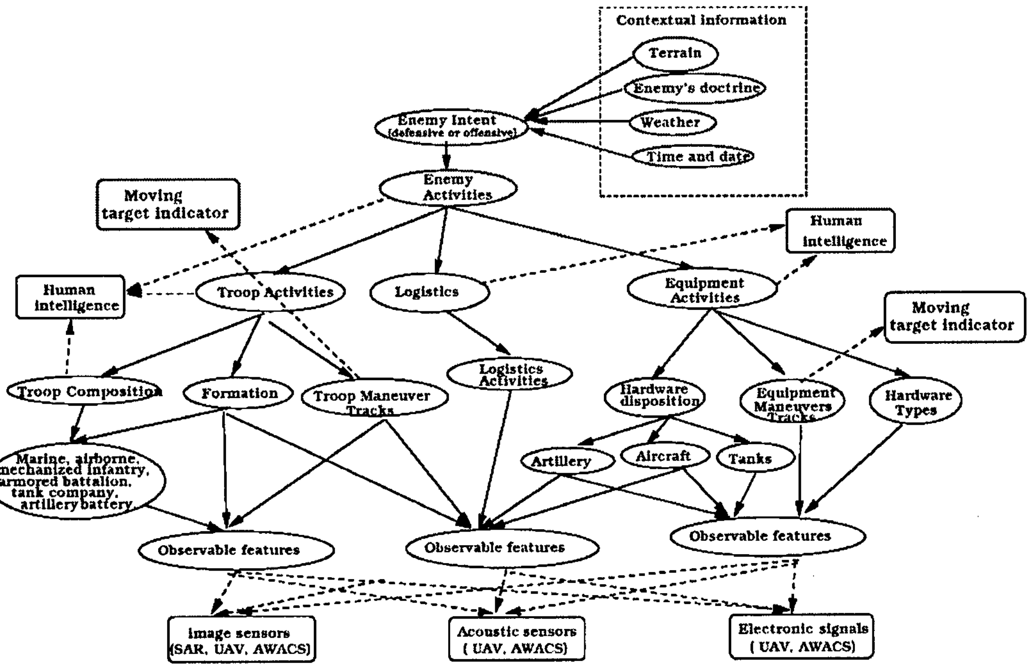


Figure 2: Generic structure of a slice of a DBN for hierarchically representing knowledge related to inferring enemy intent. Rectangular nodes represent sensors that produce the sensory data at different levels.

The benefit with DBN for knowledge representation is that the representation is in a hierarchical structure. The hierarchical knowledge representation corresponds nicely to different levels of fusion according to the Joint Directors of Laboratories (JDL) Data Fusion Model classification [SteinbergBowman01]. For example, the target node at the top stores the results of level-3 fusion while the content of the leaf nodes corresponds to the level-1 fusion. The intermediate hidden nodes correspond to results of level-2 fusion. Specifically, the level-1 nodes in the bottom are used to extract sensory measurements/features from objects of interest. The level-2 nodes in the middle fuse the spatial and temporal relationships between entities to recognize objects, their relationships, and their movement tracks. Finally, the level-3 nodes at the top perform situation assessment, enemy intent prediction, or threat assessment. Level-3 fuses the combined activity and capability of enemy forces to infer their intention and to assess the threat they pose.

While excellent in knowledge and uncertainty representation, DBNs do not have the decision making capability. Decision such as what sensory actions to take next and what course of actions to choose need be made outside the DBN framework, usually in a heuristic manner and independent of the fusion process. To overcome this limitation, we extend the framework from the DBNs to Dynamic Influence Diagrams (DIDs). Like Bayesian networks, DIDs can represent both static and dynamic uncertain knowledge in a hierarchical graphical structure, with nodes representing the random variables and directed links between nodes representing the casual relationships. Unlike DBNs, a DID also includes decision nodes that may be used to explicitly represent various actions to take in response to the results of information fusion. Decision and utility theories can then be used within the DID framework to determine the optimal actions to take. This feature is especially attractive for active sensing since DID provides a mechanism to

systematically connect decision-making with sensor management, i.e., allowing sensory management in response to decision making.

In summary, DIDs provide a unified mathematical framework for simultaneously modeling and integrating sensory data selection, sensory data fusion, situation assessment, and decision making. Such a model yields several advantages. First, it provides a coherent and fully unified hierarchical probabilistic framework for representation and integration of sensory data of different modalities at different levels of abstraction, and for decision making via inference under uncertainty. Second, it embeds both the sensors' contribution to decision-making and their operating cost in one framework to allow systematic determination of an optimal sensor subset based on utility theory, probability theory and information theory. Third, it systematically incorporates the evolution of the situation and sensory data as well as accounts for the temporal aspect of decision making with a dynamic structure. Under the framework, timely and effective decision can be made by dynamic inference based on selecting a subset of sensors with the optimal trade-off between their cost and benefit. Figure 3 shows an example of DID framework for modeling space situation awareness and space threat mitigation. Additional examples about DIDs may be found in [Liao&Ji07a, Liao&Ji06b]

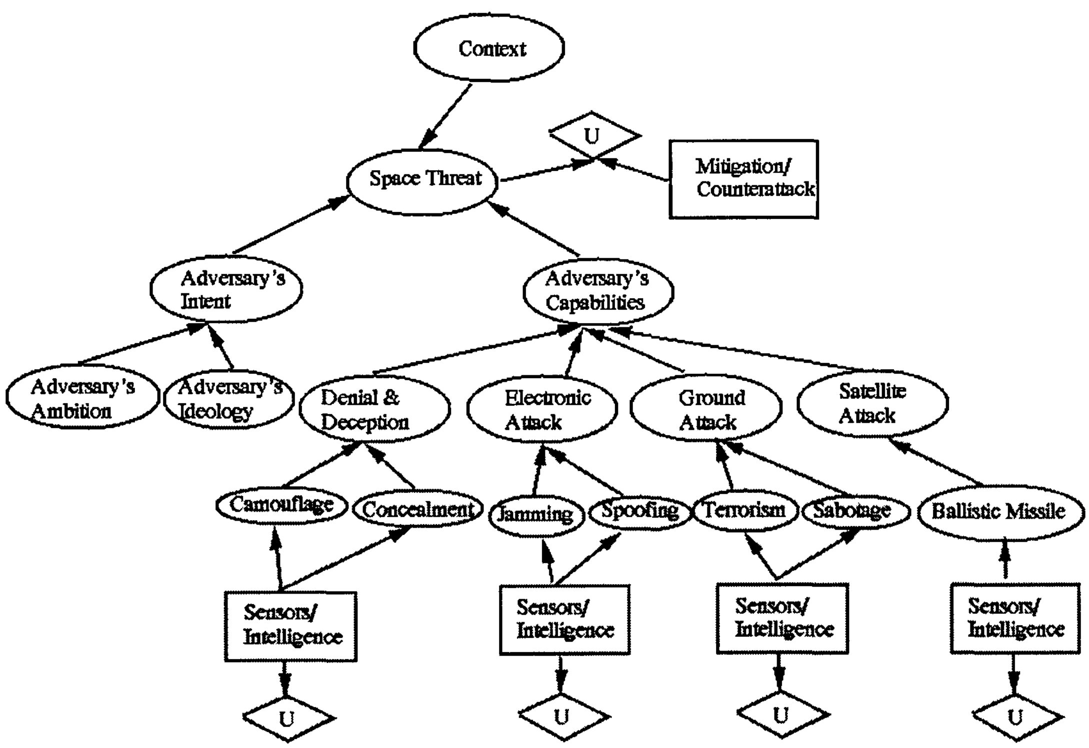


Figure 3: An example influence diagram for modeling space threat assessment and mitigation, where the circular nodes represent the random variables (like the nodes in DBN), the rectangular nodes represent the action/decision nodes (e.g. sensory action and course of action), and the diamond nodes represent the utility of the actions/decisions.

4. Model Construction and Learning with both Quantitative and Qualitative Knowledge

Given the generic DBN/DID as discussed in the previous section, a key problem with graphical modeling is to determine the model topology (the model structure) and its parameters for a particular application. Model topology determination requires identifying the appropriate random variables and their relationships. Model parameterization involves quantifying each root node (the topmost node) with a prior probability and each link with a conditional probability table (CPT) describing the conditional probability of the node given all possible outcomes for its parent(s). For a dynamic ID, we also need to specify relationships between two neighboring static slices with a transitional probability matrix.

So far, we have been using domain expert to help construct the model and to provide some initial estimation of the model parameters. To further improve the model parameters, we developed a new machine learning method [Liao&etal07] that refines the initial model parameters by combining the subjective knowledge with some training data. Study [Johansson&Falkman06] shows for many military applications training data are hard to acquire due to various reasons including security or lack of data. On the other hand, it is shown that for a given application, a number of general parameters can often be extracted from the interview with the officers and from the discussion with the military experts. This subjective knowledge may often present qualitatively instead of quantitatively in the form of relationships among some parameters of the model instead of all parameters. Two types of domain specific knowledge we use in our method are the range of some parameters and the qualitative relationships among some parameters. This kind of subjective and prior knowledge is very different from the conventionally used quantitative knowledge such as prior probability distribution on all parameters. The latter is often hard to quantify or requires strong assumptions to quantify. The qualitative knowledge, on the other hand, is often ignored due to the difficulty in incorporating them into the model. To utilize the qualitative knowledge, we developed a method that estimates the parameters of a Bayesian network under incomplete/sparse training data but with some subjective constraints. Specifically, we introduce a modified expectation maximization (EM) method that performs parameter estimation in two steps: the E-step and the M-step. The E-step allows to estimate the missing data based on the available data while the M-step allows to estimate the model parameters. The EM algorithm is modified as follows. For the M step, it is modified to incorporate qualitative prior knowledge about the parameters of the model. For example, the domain knowledge about the range of the parameters and the qualitative relationships among the parameters may be incorporated in the M step to modify the objective function and to constrain the estimated parameters within a scope.

Experiments with both synthetic and real data demonstrate significant improvement of the proposed method for estimating parameters of the Bayesian network under incomplete or sparse training data. Specifically, Figure 4 gives an example of a Bayesian Network, where the shaded nodes represent variables that do not have training data. Instead, some quantitative constraints are available for those nodes.

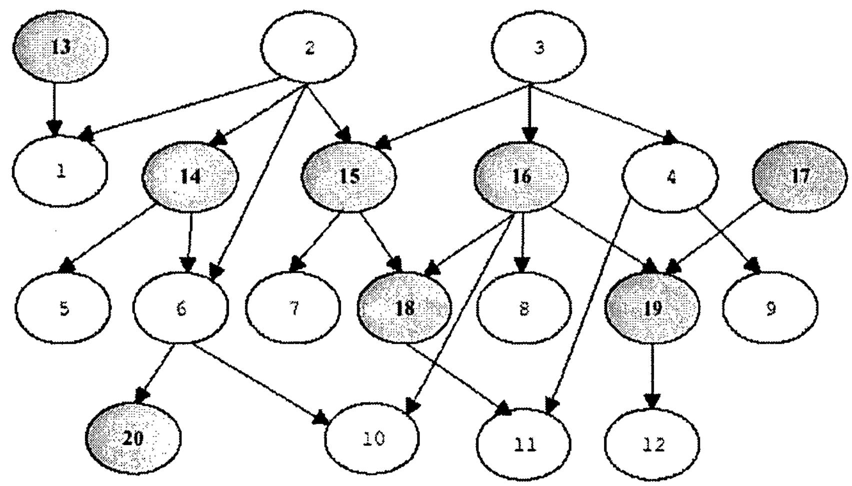


Figure 4: An example Bayesian network, with insufficient training data. Data are not available for the shaded nodes. Some qualitative subjective knowledge is available on those and other nodes.

We apply the modified EM method to estimate the parameters of the BN using the incomplete data and the qualitative constraints. The results are shown in Figure 5, where our modified EM method is compared with the results of the conventional EM method. We can see a significant improvement in the estimation accuracy in terms of the KL divergence.

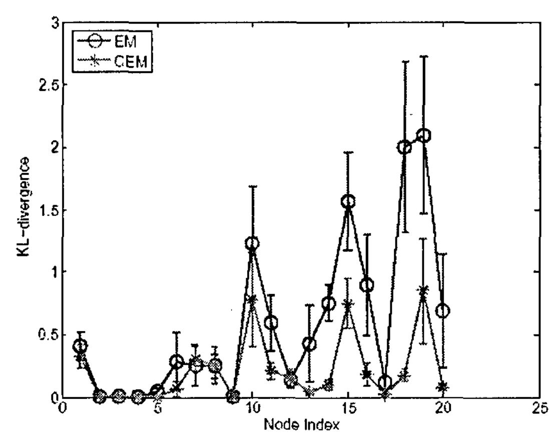


Figure 5: Results of parameter estimation using the proposed constrained EM (CEM) v.s. the conventional EM.

Additional details about the CEM method may be found in [Liao&etal07].

5. Active Information Fusion

Given the probabilistic frameworks discussed above, information fusion can be carried out through a probabilistic inference by systematically propagating the impacts of the received sensory data through the model. Belief propagation in a DID framework is usually time-consuming. Given

often a vast amount of sensory data as well as the constraints on resource and time, it is important to perform information fusion in a selective and purposive manner so that decision can be made quickly and economically. This can be achieved through active information fusion, which involves deliberate sensor management to achieve efficient, timely, and often more accurate information fusion.

As shown in Figure 6, the two main tasks for active fusion are sensor selection and sensory data fusion through belief propagation. Specifically, sensor selection is to decide which subset of sensory observations should be acquired next. Given the identified sensory observations, the corresponding sensors are activated to acquire the data, and the acquired data are subsequently integrated. Sensor selection includes two steps. The first step is achieved by designing a sensor selection criterion that represents the trade-off between the sensor benefit and sensor cost. This is then followed by the second step, which searches the sensor space using the criterion to identify the optimal sensor subset. There are significant computational difficulties associated with computing sensor selection criterion and searching for the optimal sensor subset using the criterion. In the following sections, we will discuss methods to address the two computational difficulties.

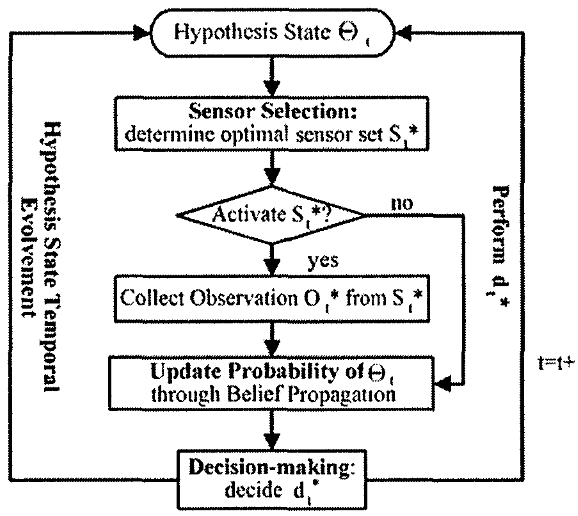


Figure 6: the steps of active fusion for decision making

5.1 Efficient Sensor Selection Criterion Computation

We have studied two sensor selection criteria: mutual information (MI) and value of information (VOI). MI defines the potential of a set of sensors in reducing the uncertainty of the current hypothesis about the situation. VOI, on the other hand, is defined as the difference of the maximum expected utilities with and without the selected information source (s) with respect to decision making. As a decision-theoretic criterion, VOI is generally different from the information-theoretic measures such as mutual information since VOI directly relates sensor/resource allocation (e.g. assignment of a reconnaissance operation) to decision-making (e.g, taking defensive/offensive actions), while information theoretic criterion relates sensor management to situation awareness. MI is therefore more suitable for situation awareness while VOI is more suitable for decision making in response to situation awareness. For this research, both MI and VOI can be used to rate the usefulness of various sensory sources with respect to the decision making, and to decide whether pieces of evidences are worth acquisition before actually activating the sensors.

Exact computation of either MI or VOI for a set of sensors is expensive and is often NP-hard, which is practically infeasible. One common solution to this problem is to use myopic approach, i.e., selecting one optimal sensor at a time. Obviously, such selection is not always reasonable since a decision maker will often not act after acquiring data from only one information source. Instead, a decision maker often needs to collect multiple pieces of evidence from multiple sources before making a decision. Therefore, it is necessary to compute non-myopic MI and VOI. Hence, an approximate computation of non-myopic VOI and MI is necessary to make its computation feasible for practical applications.

In [Zhang&Ji05], we introduce a graph-theoretic approach for efficiently approximating the mutual information for a set of sensors. Specifically, we propose a new quantitative measure for sensor synergy, based on which a sensor synergy graph is constructed. Using the sensor synergy graph, we introduce an alternative measure (the least upper bound of mutual information) to approximate multi-sensor mutual information for characterizing sensor information gain. Studies show that the new measure is very close to mutual information in value yet can be very efficiently computed. Figure 7 shows the closeness between the least (greatest) upper bound of mutual information and the exact mutual information for sensor subsets of different sizes. It is clear that the proposed criterion based on the least upper bound of mutual information closely follows the values of the exact mutual information.

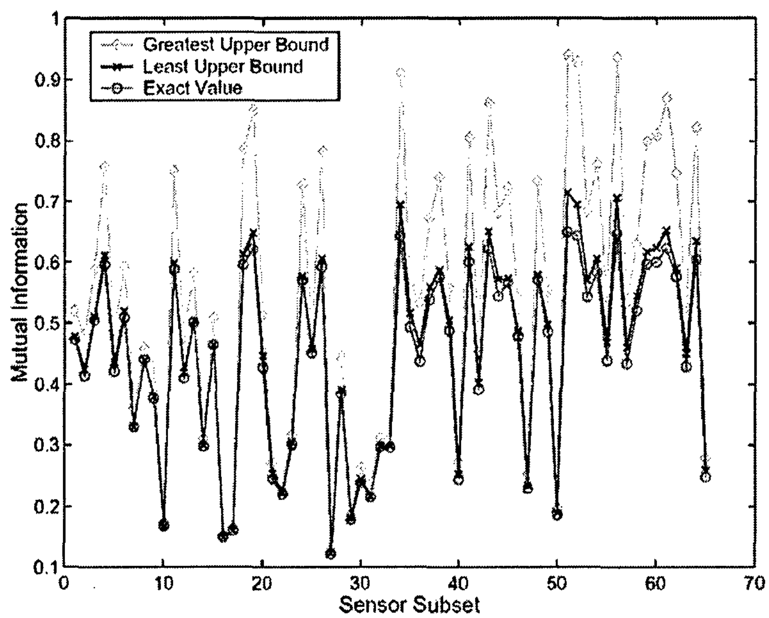
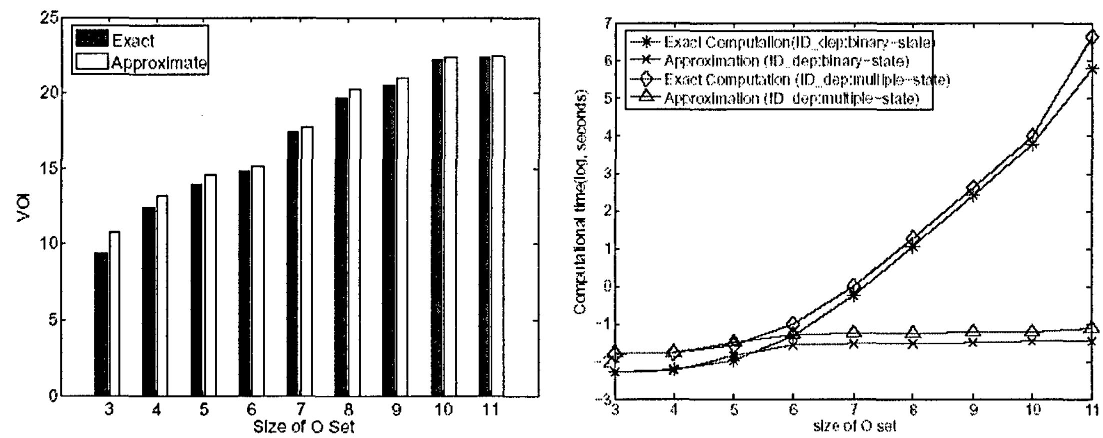


Figure 7: the closeness between the least (greatest) upper bound of mutual information and the exact mutual information for sensor subsets of different sizes.

Computationwise, since the substitute measure can be written simply as the sum of the mutual information of only pairwise sensors and singleton sensors, its computation cost is relatively very low. Therefore, the computational difficulty in computing exactly higher order mutual information can be circumvented by computing only the least upper bounds of mutual information. An extensive simulation study demonstrates both the optimality and efficiency of the sensor selection criterion. Details may be found in [Zhang&Ji05, Zhang&Ji07]

In [Liao&Ji06], we introduced an algorithm to approximately compute non-myopic VOI efficiently by exploiting the central-limit theorem as well as by exploiting the statistical

dependencies among the sensors. Specifically, computing VOI requires a sum over all possible combinations of sensory observations, which is time consuming for a large number of sensors or for sensors with many states. In our method, we treat each term in the summation as a random variable, whose mean and standard deviation can be individually estimated. The central limit theorem can then be used to approximate the mean and standard deviation of the sum, based on which VOI can be efficiently approximated. Additional computational saving is achieved by exploiting the statistical dependencies among sensors when computing mutual information. Studies with both synthetic and real data show that the approximated method for computing VOI produces significant improvement in computation speed with minimum loss in estimation accuracy. Figure 8 shows results from a simulation study, where it shows the comparison of the proposed approximated method for computing VOI against the exact VOI computation method in terms of accuracy and speed for sensor subsets of different sizes. It quantitatively demonstrates the significant improvement in computational efficiency with minimum loss in accuracy, especially for sensor sets with many sensors.



(a) (b)

Figure 8: Comparison of the exact computation of VOI v.s. the proposed approximation method for sensor subset of different sizes in terms of accuracy (a) and time (b).

5.2 Efficient Sensor Selection

Given the criterion for sensor selection, the selection of a sensor subset from several sensor candidates can be regarded as a search problem in a combinatorial space. The goal is to find the most appropriate solution among all possible sensor combinations. Since the number of sensor combinations 2^k increases exponentially with the number of sensors k, it is infeasible for an exhaustive search with even a moderate k. Various methods have been proposed to perform search efficiently but often with suboptimal solution. These methods include the greedy approach (select the top K sensors), the myopic approach (select one sensor at a time), and the heuristic methods.

We have attacked the sensor selection problems from two different aspects. First, we study the properties of sensor selection criteria under different conditions so that a greedy approach can produce performance guarantee. Specifically, our recent research proves that information-theoretic sensor selection criterion such as mutual information has the submodular property under certain conditions and given such a property, the greedy sensor selection method guarantees the near-optimal sensor selection accuracy in polynomial time [Liao&Ji07]. Using this special property, we developed a greedy sensor selection method based on mutual information that can efficiently identify the near optimal subset of sensors. Table 1 shows results of the proposed sensor selection

methods (alg1a, alg1b, and alg2) against the conventional greedy approach in terms of accuracy and speed.

Table 1: Comparison of the proposed sensor selection methods v.s. the conventional greedy sensor selection method

	Alg. 1a	Alg. 1b	Alg. 2	Greedy
Error Rate	0.06	0.06	0.10	0.22
Information gain rate	0.99	0.99	0.97	0.91
Running time rate	0.35	0.10	0.06	0.03

In table 1, the *error rate* is the ratio between the number of mis-selection cases and the overall number of cases, where a mis-selection case is defined as the case that the selected sensor set has more than one sensor different from the ground-truth. The *information gain rate* is the ratio between the mutual information of the selected sensor set and that of the optimal sensor set. The *running time rate* is the ratio between the running time of the proposed methods and that of the brute-force, averaged over 500 testing cases. It is apparent that the proposed sensor selection methods can produce more accurate results with little loss in computational speed. Additional information about this work may be found in [Liao&Ji07b].

Second, we also introduced a graphic-theoretic approach [Zhang&Ji05] to efficiently find the near optimal subset of sensors. The method first defines a sensor synergy measure, based on which a synergy graph is constructed to represent synergy among sensors. The graph is subsequently used to prune the sensor space so that a large set of less synergetic sensor combinations can be eliminated, significantly reducing sensor space and as a result, the optimal subset can be more efficiently identified in the reduced sensor space. Table 2 summarizes the results of comparison of the proposed sensor selection method with the random selection method and with the brute force method in both accuracy and time for sensor subsets of different sizes.

Table 2 Comparison of the proposed method, with the random method and the brute force method.

Number of Sensors	Our Approach		Random Method	Brute-Force
	Relative utility difference of our method to brutal force methods	Run time (Seconds)	Relative utility difference of random method to brutal force methods	Run time (Seconds)
7	1.56%	1.020	21.13%	63.87
8	1.77%	1.099	28.32%	355.05
9	2.75%	1.209	36.54%	2967.36
10	1.89%	1.430	39.19%	13560.54

It is clear from the table that compared with the random sensor selection, the proposed sensor selection method improves accuracy significantly. Against the brute force method, the speed improvement is several orders of magnitude with minimum loss in accuracy. More about this work may be found in [Zhang&Ji07].

6. Efficient Sensory Data Fusion

To fuse the information collected from the sensors for timely decision-making, an efficient belief propagation algorithm is needed since typical belief propagation based on ID/BN is NP-hard. We developed a factorization tree inference (FTI) algorithm [Liao&Ji04, Zhang&Ji06b] to efficiently integrate the acquired sensory data and to update the hypothesis belief. The algorithm factors out the computations that are common for sequential inference so that they can be computed only once, and can be applied to the subsequent inference without re-computing them, therefore significantly reducing the sensory fusion time. Details about these algorithms may be found in [Liao&Ji04, Zhang&Ji06b]. Figure 9 compares the inference efficiency of the factor tree approach with other popular inference methods. It is clear that the proposed factor free is better for sequential inference.

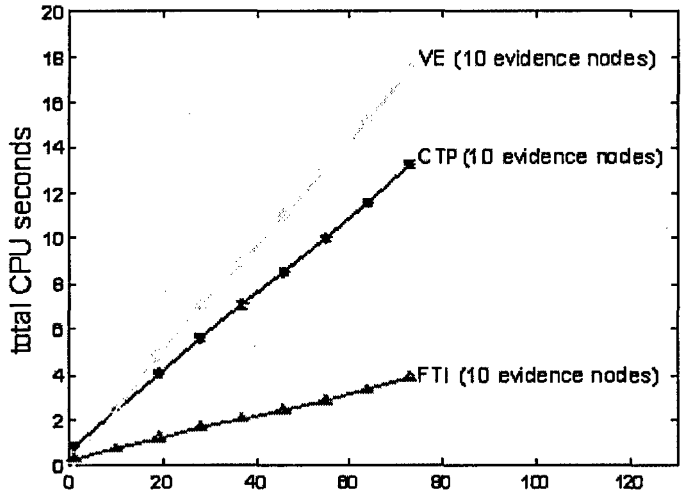


Figure 9: Comparison of factor tree approach with other inference methods (Variable Elimination (VE) and Clique Tree Propagation (CTP)) for sequential inference

7. An Application Example

The proposed framework may be used for modeling complex dynamic events, which requires efficient interpretation of data from different sources to achieve high level understanding of the causes that lead to the observed data as well as to take appropriate course of actions to alleviate the threat the situation may pose. Here, we briefly demonstrate the application of the proposed framework for a multi-stage battlefield situation assessment.

The scenario develops during a period of growing hostility between the nation A (Blue force) and the nation C (Red force). The island Mz locates between the two nations and it was occupied by the Blue force since the World War II. The Red force wants to seize the island back. As the situation worsens, the Blue force designates an area covering land and sea as a restricted zone, and declares any activities in the restricted area as hostile.

To monitor the situation, the Blue force surveillance facilities include a number of shore sensors, unmanned aerial vehicles (UAVs), surveillance helicopters (RAH66 Comanche), etc.. As hostilities break out openly, the Red force may want to destroy the surveillance facilities used by the Blue force. Further, the Red force may also pursue air strike or surface attack of the Blue force if necessary.

Using its assets, the Blue force monitors the activities of the Red force, infers its intent, and takes appropriate actions to mitigate any threat the Red force may pose. A dynamic influence diagram as shown in Figure 10 is constructed to help the Blue force to assess the intent of the Red force and to determine the best course of actions. A set of hypotheses representing possible Red force intentions include: 1) Passive: monitor the Blue forces in the restricted zone; 2) Defensive: conduct active reconnaissance and maintain a defensive presence; 3) Offensive: mount naval attack or infantry artillery engagement (surface-to-air or surface-to-surface attack) on the Blue forces with the intention of destroying the Blue forces as well as their offshore surveillance facilities. Corresponding to each enemy intent, the Blue force may take different actions.

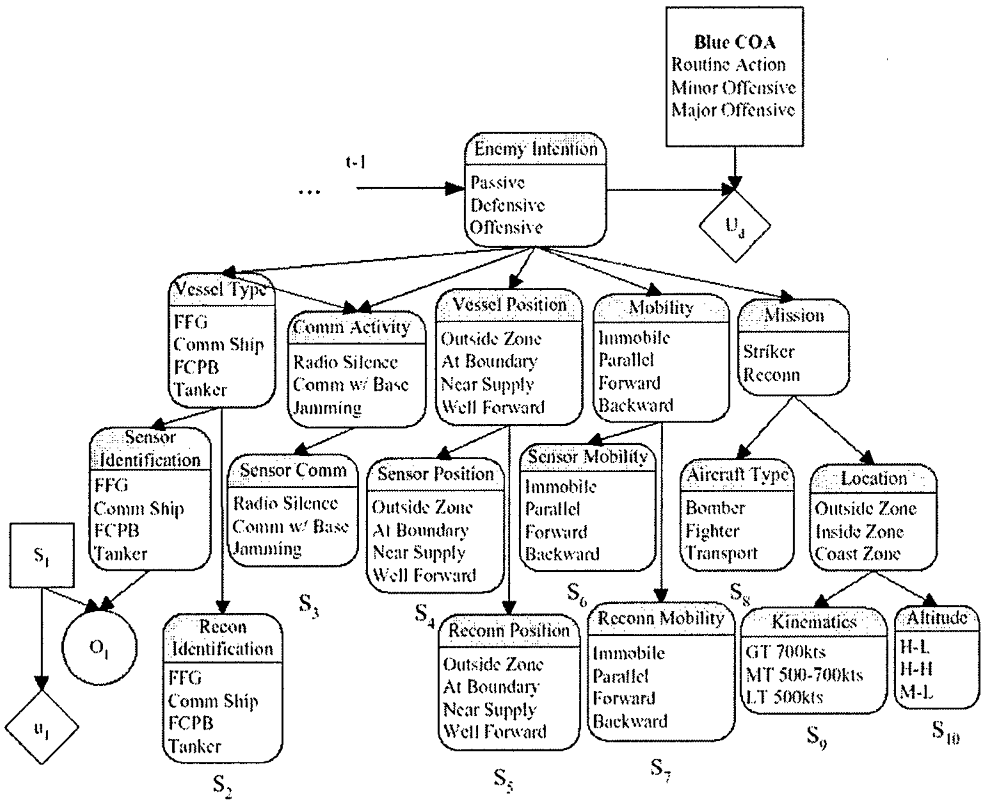


Figure 10: A dynamic influence diagram model for the battlefield scenario. S_1-S_{10} represent the surveillance facilities the Blue force uses to collect sensory data on Red force activities.

Given the model, at each time instant, we then apply the active fusion algorithms to efficiently identify the optimal sensors to use in order to timely and efficiently identify enemy intent, based on which we then decide the optimal action the Blue force can take in order to minimize any threat from the Red force. Figure 11 provides the results of inference over time about the intent of the Blue force, the sensors used by the Red force, and the actions taken to counter any threat from the Red force.

Assessment Stage	Probability of Hypothesis	Blue Force Action Taken	Sensors Selected
1	P(Pas)=0.3333 P(Def)=0.3333 P(Off)=0.3333	Observe	S_4, S_5, S_9 S_{10}, S_7 S_{12}
2	P(Pas)=0.7379 P(Def)=0.1367 P(Off)=0.1253	Further Observe	S_9, S_{10}
3	P(Pas)=0.7465 P(Def)=0.1327 P(Off)=0.1208	Interception (Red Force may Change Intention)	
4	P(Pas)=0.2590 P(Def)=0.5518 P(Off)=0.1892	Further Observe	S_5, S_7 S_9, S_{10}
5	P(Pas)=0.2164 P(Def)=0.6877 P(Off)=0.0959	Further Observe	S_5, S_7 S_8, S_{11} S_{12}
6	P(Pas)=0.0213 P(Def)=0.8381 P(Off)=0.1406	Minor Offensive (Red Force May Change Intention)	

Figure 11 Step by step inference results for the example

Details about this example may be found in [Zhang & Ji05,Liao&Ji07b].

8. Active Information Fusion Demo Software

Besides the application, we have also developed a real-time prototype software to demonstrate the proposed methods. In the demo software, several sensor selection algorithms discussed in section 5.2 are implemented including the greedy approach, the graph-theoretic approach, the myopic approach, the random approach, and the brutal force approach. User can change the model parameters, the reliability and cost for each sensor. Then, based on the inputs, the system returns the selected sensors by using different sensor selection algorithms. The returned results are displayed so that the user can compare the efficiency and accuracy of different algorithms. We have two versions of the demo software: one is based on the graph-theoretic approach that uses only mutual information as the selection criterion and the other is based on the greedy sensor selection approach that uses either mutual information or value of information as the selection criteria. Figure 12 shows the interface for the software based on the graph-theoretic approach. Figure 13 shows the interface for the software based on the greedy approach.

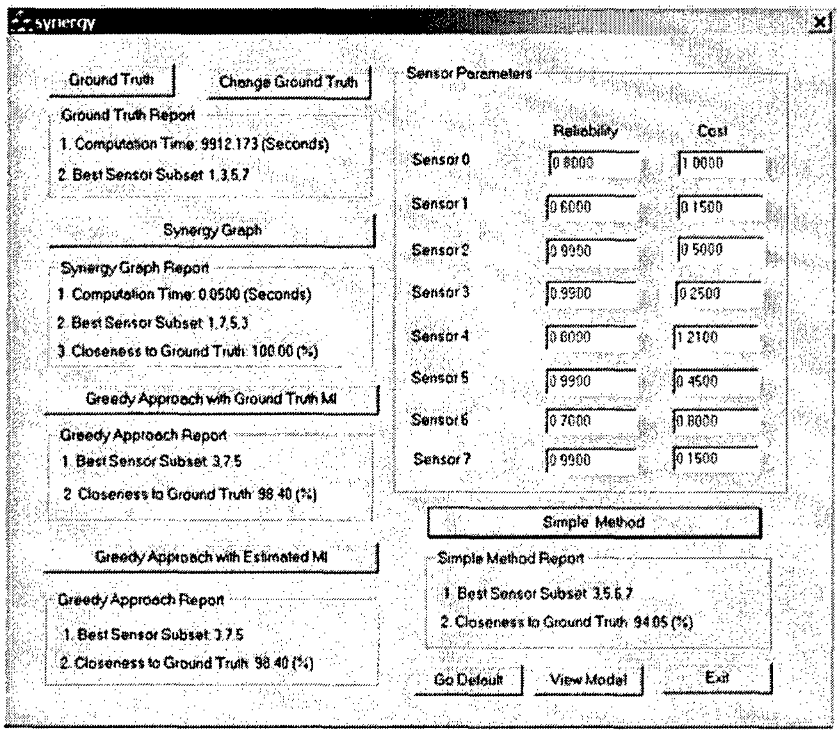


Figure 12: The active fusion demo software interface that uses mutual information as sensor selection criterion and uses the graph-theoretic approach for sensor selection.

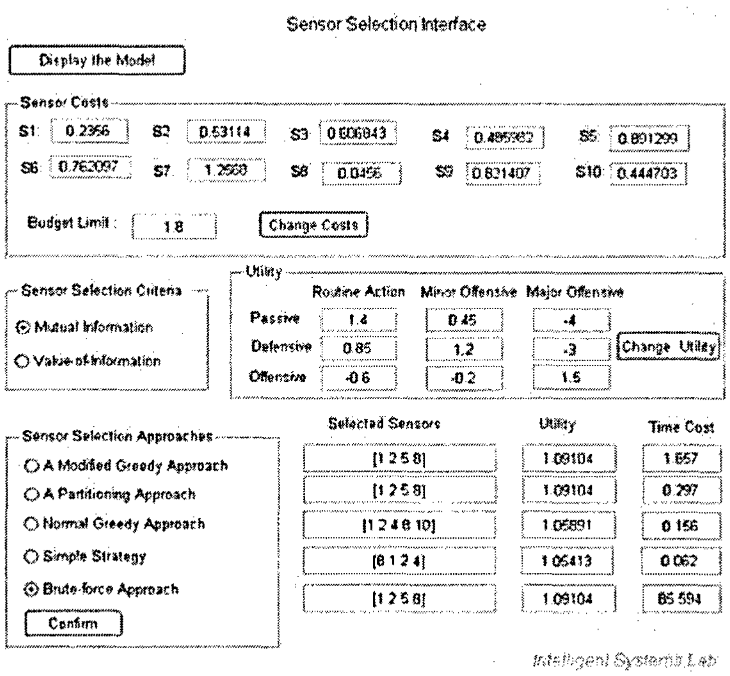


Figure 13: The active fusion demo software interface that uses either mutual information or value of information as sensor selection criteria and uses the greedy approach for sensor selection.

Both software are available to the government upon request.

9. Interaction/Transitions

Over the past few years, the PI actively interacted with the AFRL-Rome lab to identify new applications for the proposed theories and algorithms. Specifically, the proposed active fusion strategy has been applied to addressing the computational complexity problem plaguing AFRL-Rome's Causal Analysis Tool (CAT) for military plan assessment, leading to a significant computational saving for military plan evaluation [Zhang&Ji06b].

Finally, through this project, we have provided complete financial support for one Ph.D student, partial support for another Ph.D student, and financial support for two postdoctoral associates. In particular, one Ph.D student (Ms. Wenhui Liao) received her Ph.D in December, 2006 with complete financial support from this grant. Her dissertation is on high level active information fusion.

10. Conclusion

In summary, through this research we made several contributions as summarized below:

1) Developed and implemented a unified probabilistic framework for simultaneously modeling sensory data, sensor selection, situation assessment, and decision making. Specifically, we studied and implemented two frameworks: Dynamic Bayesian Networks and Dynamic Influence Diagrams.
2) Developed and implemented a learning algorithm to estimate model parameters when data are incomplete using domain specific qualitative knowledge. Specifically, we developed a constrained Expectation-Maximization learning algorithm for learning the parameters of the Bayesian network under incomplete/sparse training data with qualitative constraints.
3) Introduced sensor selection criteria and develop computational methods to efficiently compute the criterion. We studied two sensor selection criteria (mutual information and value of information) and developed methods to efficiently compute them
4) Developed active sensor selection methods to efficiently identify a subset of optimal sensors
    a. a greedy approach based on submodular property of mutual information with performance guarantee
    b. a graph-theoretic approach to systematically estimate synergy among sensors and to significantly reduce the sensor search space by eliminating a large number of unpromising sensor combination through a synergy graph.
5) Developed a belief propagation method to efficiently integrate the acquired sensory data and update the belief to current hypothesis. Specifically, we introduced a factorization method for efficient sequential inference in both BN and ID.
6) Demonstrated the feasibility of the framework and algorithms with realistic military applications. Developed user-friendly prototype software for this purpose.
7) Worked with AFRL/Rome lab to apply the proposed active fusion methods to address the military plan assessment problem.
8) Produced one Ph.D dissertation and 10 publications in the referred journals and conferences.

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